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Characteristics of Speed Sensorless Vector Controlled Induction Motor with High Efficiency Taking Core Loss into Account

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Abstract

This paper presents the characteristics of a speed sensorless vector control method of an induction motor operating at high efficiency and high response, in which core loss is taken into account. An improved method of speed estimation that operates on the principle of speed adaptive flux and current observer has been proposed. An observer is basically an estimator that uses a plant model and a feedback loop with measured stator voltage and current. Simulation results show that the proposed direct field oriented control with the proposed observer provides good performance characteristics. The IM is fed by an indirect power electronics converter. This indirect converter is controlled by a pulse width modulation PWM technique that enables minimization of harmonics introduced by the line converter, as well as the control of the power factor and DC-link voltage. We study the robustness of the overall system- using simulation of different modes to operating modes and varied parameters.

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Keywords: Induction motor; Core loss; Direct field oriented control; Estimation; Extended Kalman filter; High efficiency.

1. INTRODUCTION

The conventional field-oriented method of controlling an induction motor ignores core loss. However, in practice, core loss causes the rotor current and rotor flux to interfere with each other[1]. This makes the output torque different

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from the reference torque. To solve this problem, we have also proposed a method of compensating for core loss to ensure that the rotor flux and rotor current do not affect each other.

Research interest in induction motor (IM) sensorless drives has grown significantly over the past few years due to some of their advantages, such as mechanical robustness, simple construction, and maintenance. Present efforts are devoted to improve the sensorless operation, especially for low speed and to develop robust control strategies.

Direct and indirect vector control methods for the speed and torque control of IM have found intensive application through the last two decades. For the indirect control of IM, in addition to the rotor speed, accurate knowledge of the slip frequency (calculated as a function of the IM parameters) is required. On the other hand, direct control of IM necessitates accurate information on the rotor speed, as well as rotor flux as referred to the stator stationary frame[2,3,4].

However, the possibility of using the EKF structure but making a direct parameterization of the observer gain matrix. Variants of this approach has been suggested by e.g. by Kubota et al[5], Nilsen and Kaimierkowski[6], Peterson[7], and Harnefors and Nee[8].

This paper present a method of estimation of speed and flux of induction motors with taking core loss into account based on EKF. The paper is organized as follows. Section 2 describes the model of induction motor model with taking core loss into account. In Section 3 an estimator using EKF for the speed and flux is designed. Simulations of the scheme are carried out in Section 4 and some conclusions are given in Section 5.

2. INDUCTION MOTOR MODEL

For the purpose of using EKF for the estimation of the rotor flux of an induction machine; it is possible to use various machine models. For example, it is possible to use the equations expressed in the rotor flux-oriented reference frame, or in stator flux-oriented reference frame. In order to avoid extra calculations and non-linear transformations, stationary reference frame is preferred. The main advantages of using the model in stationary reference frame are reduced computation time, smaller sampling time, higher accuracy, more stable behaviour[1]. Thus, we have chosen stationary reference frame in our study. So, the proposed model for induction motor with high efficiency taking core loss into account is shown in fig 1.

Assuming that core loss occurs due to the eddy current, the induction motor model can be as shown in Fig. 1. In this figure, eddy current is assumed to flow in d, q winding. The formula for the voltage of an induction motor in which stator core loss is taken into consideration is given by (l), in the rotating reference frame[1,5]

$$\begin{cases} \bar{V}_s = R_s \bar{I}_s + \dfrac{d}{dt}\bar{\phi}_s + j\omega_s \bar{\phi}_s + R_{fs}(\bar{I}_s + \bar{I}_r) \\ 0 = R_r \bar{I}_r + \dfrac{d}{dt}\bar{\phi}_r + j\omega_r \bar{\phi}_r + R_{fs}(\bar{I}_s + \bar{I}_r) \end{cases} \tag{1}$$

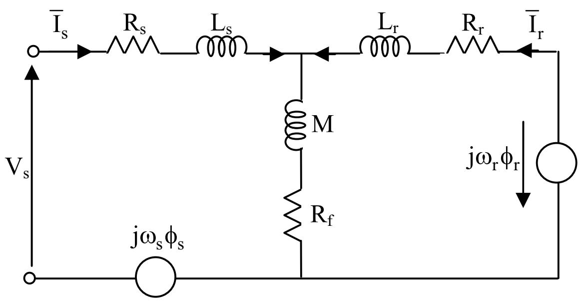

Fig. 1. Equivalent circuit for the IM with taking core loss into account.

Nomenclature

$V_{s\alpha,\, s\beta}$	stator voltage
$i_{s\alpha,\, s\beta}$	stator current
$i_{r\alpha,\, r\beta}$	rotor current
Ls, Lr	stator and rotor self inductance
Rs , Rr	stator and rotor resistance
Ω	mechanical rotor speed
P	number of pole pairs
ϕ_s	stator flux
ϕ_r	rotor flux
A, B	gains.
Rf	core loss resistance
σ	total leakage factor
T_s	sampling interval
W	slip frequency
F	stator frequency

The torque is given by

$$T_e = \frac{3pL_m}{2L_r}(\phi_{rd}.i_{sq} - \phi_{rq}.i_{sd}) \tag{2}$$

The core loss resistance is function of frequency and flux level. But the change of R_f, value depends on the variation of frequency more than that of rotor flux. Therefore, R_f is approximately a function of frequency and gains A, B.

$$R_f = A.f + B.f^2 \tag{3}$$

Where: $\delta = 1 - \frac{M^2}{L_r L_s}$, $T_r = \frac{L_r}{R_r}$, $T_s = \frac{L_s}{R_s}$

The model of the induction motor takes core loss into account. Expressed in the Park reference frame is given in the suitable state form[2,5]

$$\begin{cases} V_{ds} = (R_s + \frac{L_{\delta r}}{L_r} R_{fs}) i_{ds} + \delta L_s \frac{di_{ds}}{dt} + \frac{R_{fs}}{L_r}\phi_{dr} + \frac{M}{L_r}\frac{d\phi_{dr}}{dt} \\ V_{qs} = (R_s + \frac{L_{\delta r}}{L_r} R_{fs}) i_{qs} + \delta L_s \frac{di_{ds}}{dt} + \frac{R_{fs}}{L_r}\phi_{qr} + \frac{M}{L_r}\frac{d\phi_{qr}}{dt} \\ 0 = (\frac{L_{\delta r}}{L_r} R_{fr} - \frac{M}{T_r}) i_{ds} + \frac{R_r + R_{fr}}{L_r}\phi_{dr} + \frac{d\phi_{dr}}{dt} + \omega_r \phi_{qr} \\ 0 = (\frac{L_{\delta r}}{L_r} R_{fr} - \frac{M}{T_r}) i_{qs} + \frac{R_r + R_{fr}}{L_r}\phi_{qr} + \frac{d\phi_{qr}}{dt} + \omega_r \phi_{dr} \end{cases} \tag{4}$$

3. DESIGN OF EKF OBSERVER

Accurate and robust estimation of motor variables which are not measured is crucial for high performance sensorless drives. A multitude of observers have been proposed, but only a few are able to sustain persistent and accurate wide speed range sensorless operation. At very low speed, theirs performances are poor. One of the reasons is the high sensitivity of the observers to unmodeled nonlinearities, disturbance and model parameters detuning.

The Kalman filter provides a solution that directly cares for the effects of disturbance noises including system and measurement noises. The errors in parameters will also normally be handled as noise[9].

The dynamic state model for non non-linear stochastic machine is as follows where all symbols in the formulations denote matrices or vectors[10,11]

$$\begin{cases} \dot{x}(t) = f(x(t), u(t), t) + w(t) \\ y(t) = h(x(t), t) + v(t) \end{cases} \tag{5}$$

$w(t)$: System noise vector.

$v(t)$: Measurement noise vector

w, v : are unrelated and zero mean stochastic processes.

A recursive algorithm is presented for the discrete time case. For the given sampling time T_s, both the optimal estimate sequence $x_{k/k}$ and its covariance matrix $P_{k/k}$ generated by the filter go through a two step loop.

The first step (prediction) performs a prediction of both quantities based on the previous estimates $x_{k-1/k-1}$ and the mean voltage vector actually applied to the system in the period from T_{k-1} to T_k .F is the system gradient matrix (Jacobean matrix).

$$F(\tilde{x}(t), t) = \left. \frac{\partial f(x(t), u(t), t)}{\partial x^T(t)} \right|_{x(t)=\tilde{x}(t)} \tag{6}$$

$$x_{k/k-1} = x_{k-1/k-1} + T_s.f(x_{k-1/k-1}, u_{k-1}) \tag{7}$$

$$P_{k/k-1} = P_{k/k-1} + (FP_{k-1/k-1} + P_{k-1/k-1}F^T).T_s + Q \tag{8}$$

The second step corrects the predicted state estimate and its covariance matrix trough a feedback correction scheme that makes use of the actual measured quantities; this is realized by the following recursive relations

$$x_{k/k} = x_{k/k-1} + K_k(Y_k - Hx_{k/k-1}) \tag{9}$$

$$P_{k/k} = P_{k/k-1} - K_k HP_{k/k-1} \tag{10}$$

Where the filter gain matrix is defined by

$$k_k = P_{k/k-1}H^T(HP_{k/k-1}H^T + R)^{-1} \tag{11}$$

H is transformation matrix

$$H(\tilde{x}(t), t) = \left. \frac{\partial h}{\partial x} \right|_{x(t)=\tilde{x}(t)} \tag{12}$$

The proposed EKF observer (fig 2) is designed in rotor reference frame (α, β frame).

where k/k denotes a prediction at time k based on data up to time k. similarly, (k+1)/k denotes a prediction at time k+1 based on data up to time k.

The discrete model of the IM can be given as follows

$$\begin{aligned} x(k+1) &= f(x(k), u(k)) + w(k) = A_d x(k) + B_d U(k) + W(k) \\ y(k) &= h(x(k)) + V(k) = C_d x(k) + V(k) \end{aligned} \tag{13}$$

With: w(k) is the measurement noise and v(k): is the process noise, A_d, B_d and C_d matrix of discrete system.

The state vector is chosen to be:

$$A_d = e^{AT_s} \approx I - AT_s;\ B_d = \int_0^{T_s} e^{A\tau} B\, d\tau \approx BT_s; C_d = C \tag{14}$$

I: identity matrix of system depending on the size of the state vector.

$x = \begin{bmatrix} i_{s\alpha} & i_{s\beta} & \psi_{r\alpha} & \psi_{r\beta} & \Omega \end{bmatrix}^t;\ u = \begin{bmatrix} u_{s\alpha} & u_{s\beta} \end{bmatrix}^t;\ y = \begin{bmatrix} i_{s\alpha} & i_{s\beta} \end{bmatrix}^t$

The critical step in the *EKF* is the search for the best covariance matrices Q and R have to be set-up based on the stochastic properties of the corresponding noise. The noise covariance R accounts for the measurement noise introduced by the current sensors and quantization errors of the A/D converters[12,13,14]. Increasing R indicates stronger disturbance of the current. The noise is weighted less by the filter, causing also a slower transient performance of system.

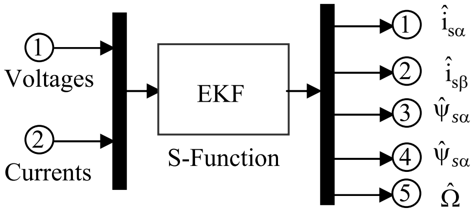

Fig. 2 . S-Function representation of the EKF.

The noise covariance Q reflects the system model inaccuracy, the errors of the parameters and the noise introduced by the voltage estimation[15,16,17]. Q has to be increased at stronger noise driving the system, entailing a more heavily weighting of the measured current and a faster transient performance.

An initial matrix P_0 represents the matrix of the covariance in knowledge of the initial condition. Varying P_0 affects neither the transient performance nor the steady state condition of the system.

In this study, the value of these elements is tuned “manually”, by running several simulations. This is maybe one of the major drawbacks of the Kalman filter.

4. SIMULATION RESULT

To verify the effectiveness of the proposed scheme, simulations were conducted in Simulink. The extended Kalman speed and flux estimation is applied to an induction motor direct field oriented controlled as shown in fig.3.

In fig. 3, Assumed the reference flux is constant with the value of 1 Wb, and the reference speed and load is 157rad/s and 10N.m respectively.

The outputs of a PWM voltage source inverter are used as the control inputs for the EKF. These signals contain components at high frequencies, which are used as the required noise by the Kalman filter. Thus, no additional external signals are then needed.

Fig.4. shows the step response of speed with 0.6 a time rating load (5Nm). The real speed and the estimated speed are shown in fig.4.a. when the references of 100 rd/s with the load torque, are given.

We can notice the good estimation of the motor speed with a few rd/s error in steady state and when load applied which illustrated by fig 4.b.

Fig.4.c shows the real and estimated flux module and the error between real and estimated flux is dressed in fig.4.d.

From fig.5, we can notice that the proposed EKF works in very low speed region, where many speed estimators or observers have poor performances. Finally, all these results confirm that EKF’s performance is quite good under no load, full load and in speed estimation for all quadrants without causing instability.

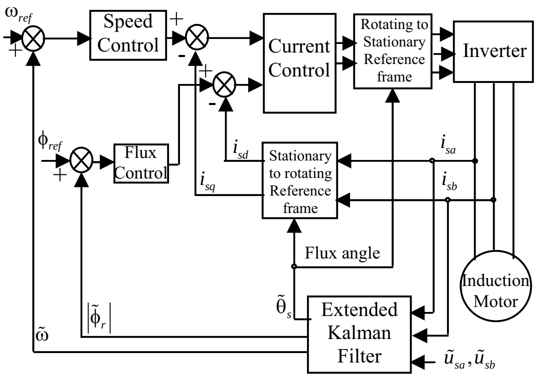

Fig.3. Speed control of an induction machine using direct field oriented control method and an EKF for rotor flux and speed estimation.

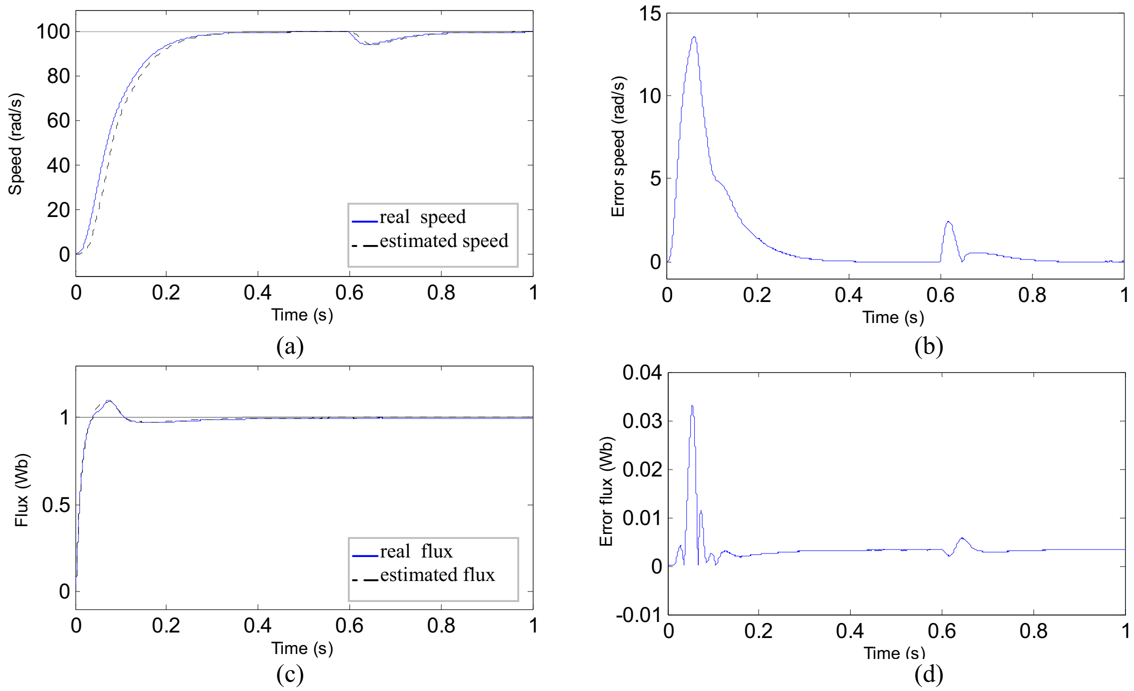

Fig.4. Step response with application of torque at the 0.6 s.

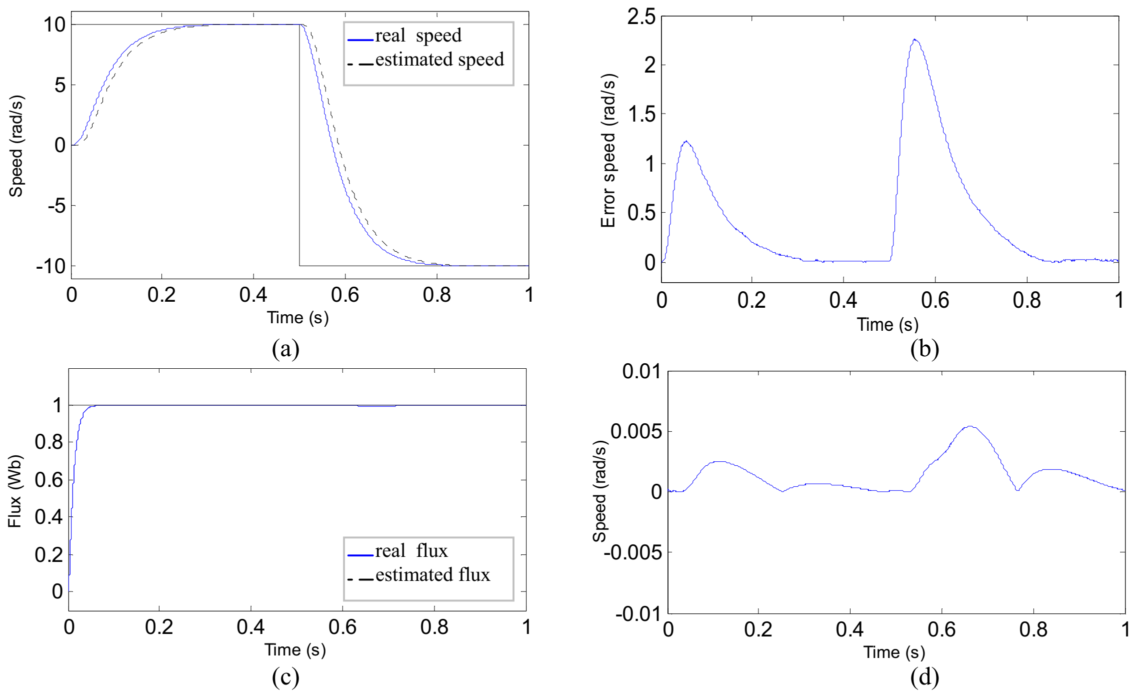

Fig.5. Low speed reversion from 10 rd/s to -10 rd/s.

5. MEASUREMENT NOISE

In many applications, the measurement noise caused by either hardware or environment affects the system significantly. The estimated states or sensed variables are the inputs into the nonlinear control. These states or variables are offen multiplied with other states or constant coefficients and amplified which degrades the outputs of the system. In this case, the filtering characteristic of the observer becomes more critical. Since the Kalman filter has the measurement noise uncertainty modeling property, one can eliminate measurement noise up to a certain limit. The estimation accuracy of EKF is tested in this paper under noisy current measurement.

In Fig 6, the injected noise to the d and q stator currents in the range of [0- 2 A] is shown. The noise is zero mean, white Gaussian. The aim of the current injection is to observe the low pass filter characteristics of EKF.

Fig 7 (overleaf) shows the responses of the speed, the currents and the flux between the actual and estimated states for step reference with 75% of the rated load at t=0.5 s. At t=1.2 s the speed is reversed from +100rad/s to -100rad/s and at t=2.2 s, the reference speed becomes 10 rad/s. As shown in Figure. 7, the estimated speed, currents, and flux are not affected too much from the injected noise. The state estimation accuracy may be increased by increasing the measurement noise covariance under noisy conditions thus the system model will have more importance.

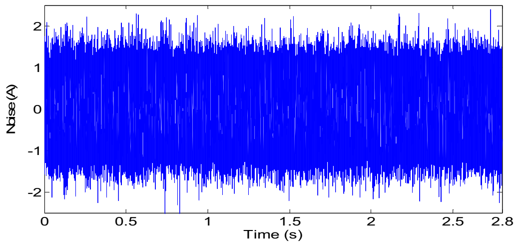

Fig.6. Injected noise to the currents of IM.

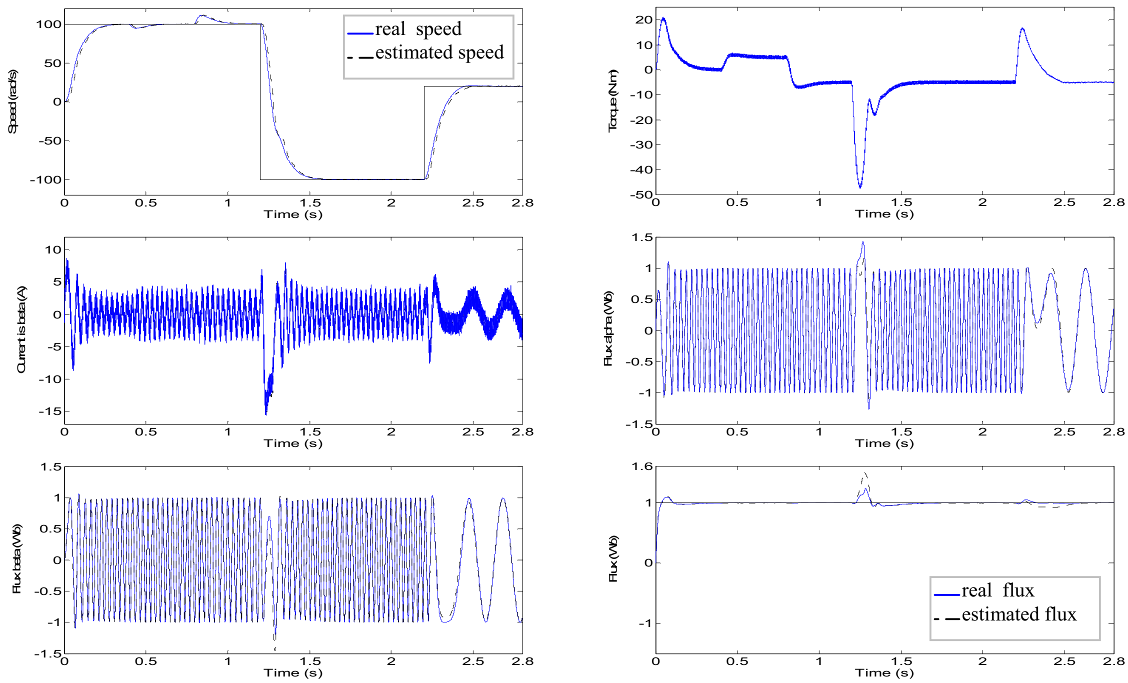

Fig.7. IM estimated and actual speed, currents, flux and torque.

6. CONCLUSION

The extended Kalman filter has been used for the speed sensorless direct vector control of an induction motor, the knowledge of the rotor space vector position is essential to implement the direct field-oriented control strategy to induction motor drives.

In this paper, a simple estimation algorithm based on EKF in direct vector control with taking core loss into account has been presented. Good results are obtained through the simulations performed under loads variation, references variation and low speed. The effectiveness and the validity of the proposed EKF estimator are verified.

Appendix

Parameters of the system used in simulation:
Type: three-phase, 0.75 Kw. 220/380V, squirrel-cage induction motor.

$R_s = 10\Omega;\ R_r = 6.3\Omega;\ L_s = 0.6560H;\ L_r = 0.6530H;$

$L_m = 0.613H; J = 0.02Kg.m^2;\ f_r = 0Nm.s/rd;$

$p = 2; T_l = 5Nm;\ \Omega = 146Rd/s.$

Supply's voltage and frequency: 220 V(rms), 50 Hz
Line's inductor and resistance 0.002 H, 0.08 Ω
Output capacitors 0.0025 F
PWM carrier frequency 1 kHz

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